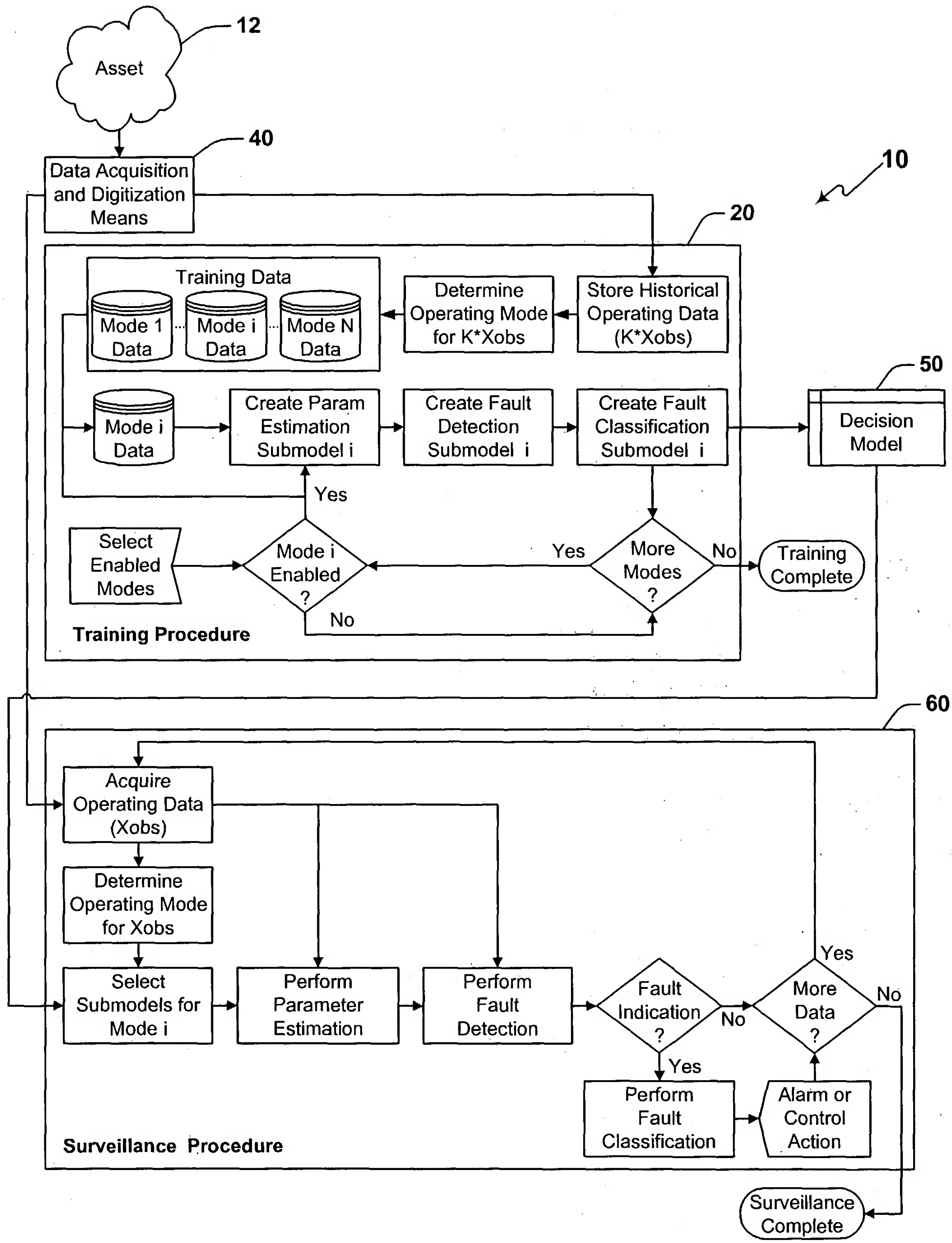


Asset
12
40
Data Acquisition and Digitization Means
10
20
Training Data
Mode 1 Data
Mode i Data
Mode N Data
Determine Operating Mode for K*Xobs
Store Historical Operating Data (K*Xobs)
50
Mode i Data
Create Param Estimation Submodel i
Create Fault Detection Submodel i
Create Fault Classification Submodel i
Decision Model
Yes
Select Enabled Modes
Mode i Enabled ?
Yes
More Modes ?
No
Training Complete
No
Training Procedure
60
Acquire Operating Data (Xobs)
Determine Operating Mode for Xobs
Select Submodels for Mode i
Perform Parameter Estimation
Perform Fault Detection
Fault Indication ?
No
Yes
More Data ?
No
Yes
Perform Fault Classification
Alarm or Control Action
Surveillance Procedure
Surveillance Complete

Figure 1

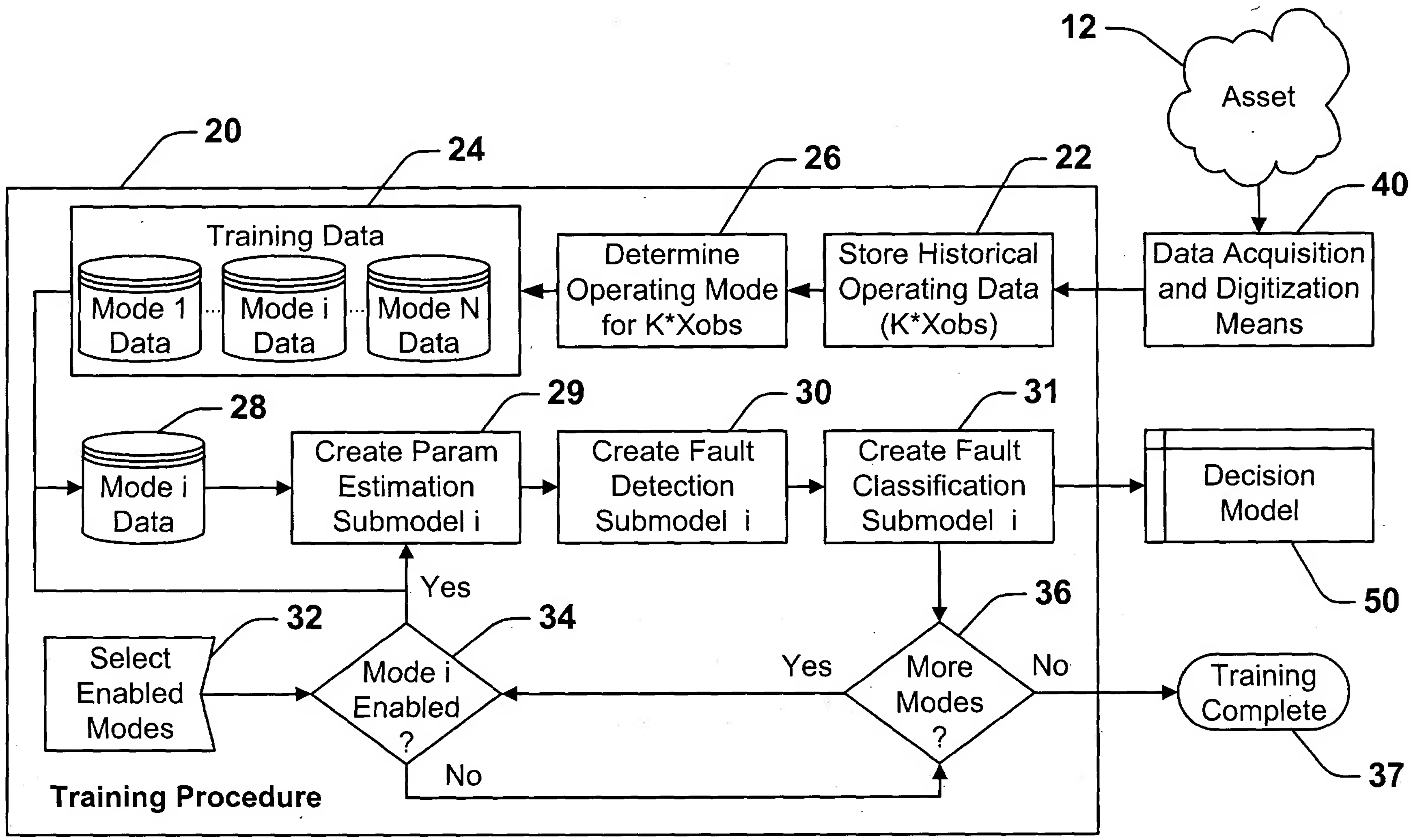

12
Asset
20
24
26
22
40
Training Data
Mode 1 Data
Mode i Data
Mode N Data
Determine Operating Mode for K*Xobs
Store Historical Operating Data (K*Xobs)
Data Acquisition and Digitization Means
28
29
30
31
Mode i Data
Create Param Estimation Submodel i
Create Fault Detection Submodel i
Create Fault Classification Submodel i
Decision Model
50
Yes
32
34
36
Select Enabled Modes
Mode i Enabled ?
Yes
More Modes ?
No
Training Complete
No
37
Training Procedure

Figure 2

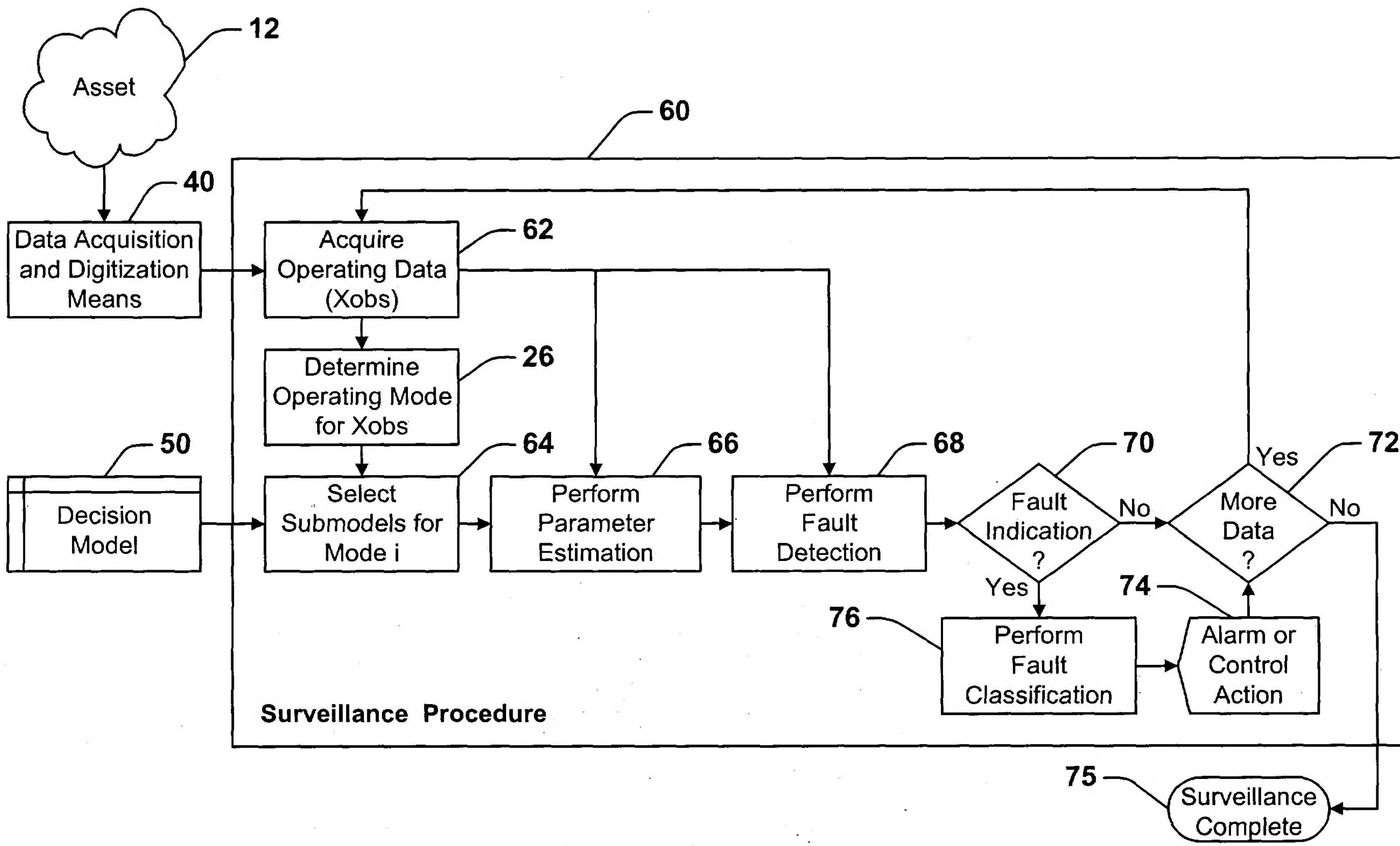

12
Asset
40
Data Acquisition and Digitization Means
60
Acquire Operating Data (Xobs)
62
Determine Operating Mode for Xobs
26
50
Decision Model
Select Submodels for Mode i
64
Perform Parameter Estimation
66
Perform Fault Detection
68
Fault Indication ?
70
No
Yes
More Data ?
72
Yes
No
74
76
Perform Fault Classification
Alarm or Control Action
Surveillance Procedure
75
Surveillance Complete

Figure 3

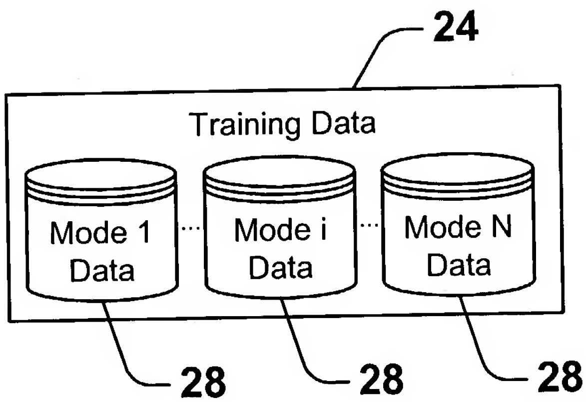


Figure 4

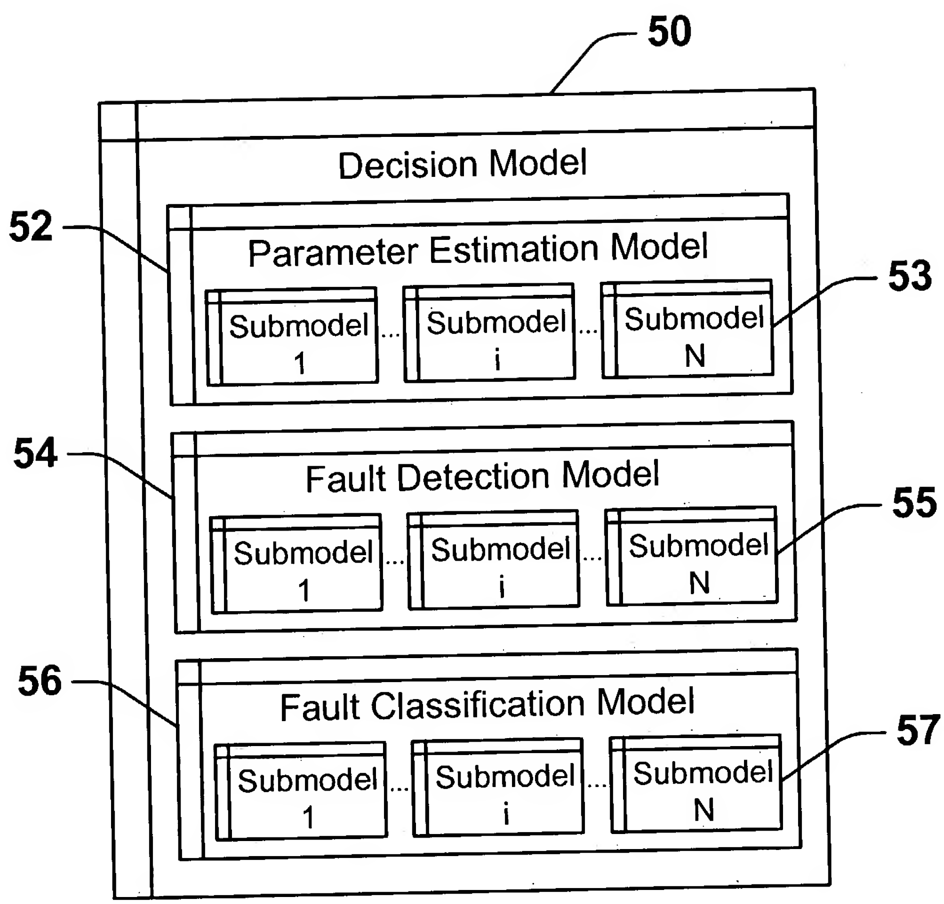

50
Decision Model
52
Parameter Estimation Model
Submodel 1
Submodel i
Submodel N
53
54
Fault Detection Model
Submodel 1
Submodel i
Submodel N
55
56
Fault Classification Model
Submodel 1
Submodel i
Submodel N
57

Figure 5

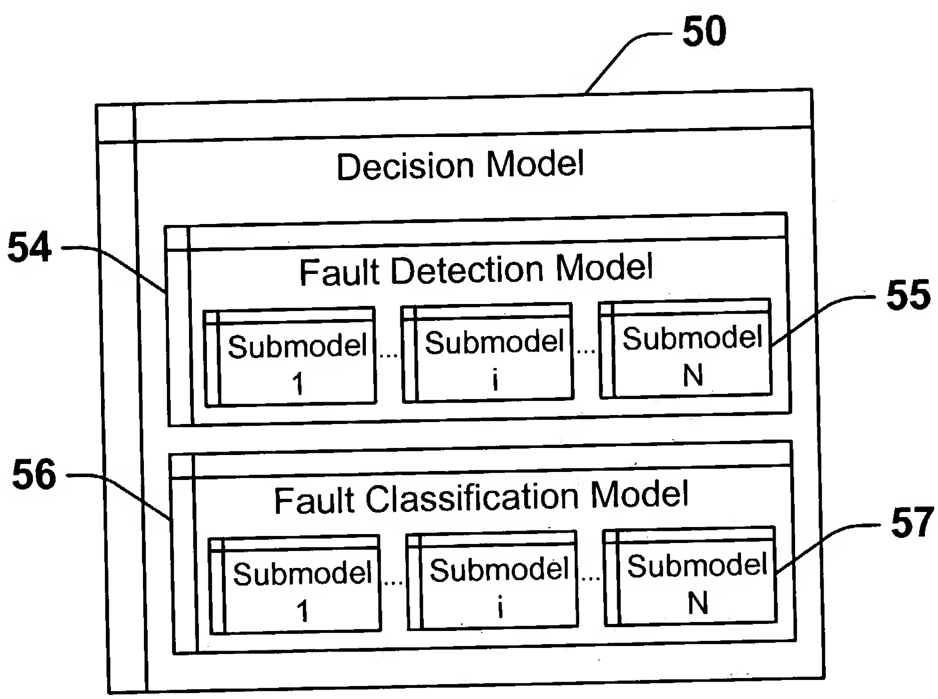
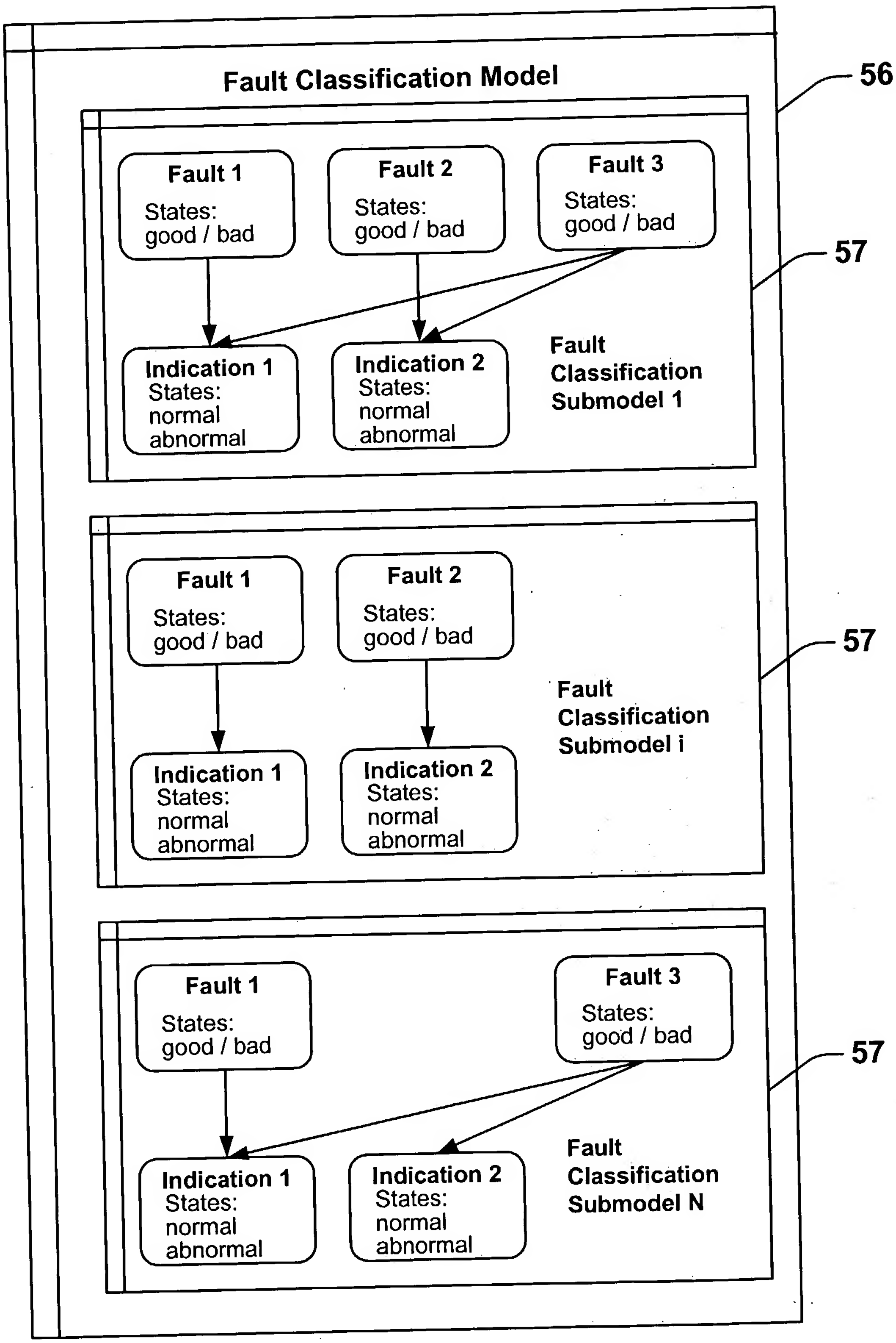

50
Decision Model
54
Fault Detection Model
Submodel 1
...
Submodel i
...
Submodel N
55
56
Fault Classification Model
Submodel 1
...
Submodel i
...
Submodel N
57

Figure 6



Fault Classification Model
56
Fault 1
States:
good / bad
Fault 2
States:
good / bad
Fault 3
States:
good / bad
57
Indication 1
States:
normal
abnormal
Indication 2
States:
normal
abnormal
Fault Classification Submodel 1
Fault 1
States:
good / bad
Fault 2
States:
good / bad
57
Fault Classification Submodel i
Indication 1
States:
normal
abnormal
Indication 2
States:
normal
abnormal
Fault 1
States:
good / bad
Fault 3
States:
good / bad
57
Indication 1
States:
normal
abnormal
Indication 2
States:
normal
abnormal
Fault Classification Submodel N

Figure 7

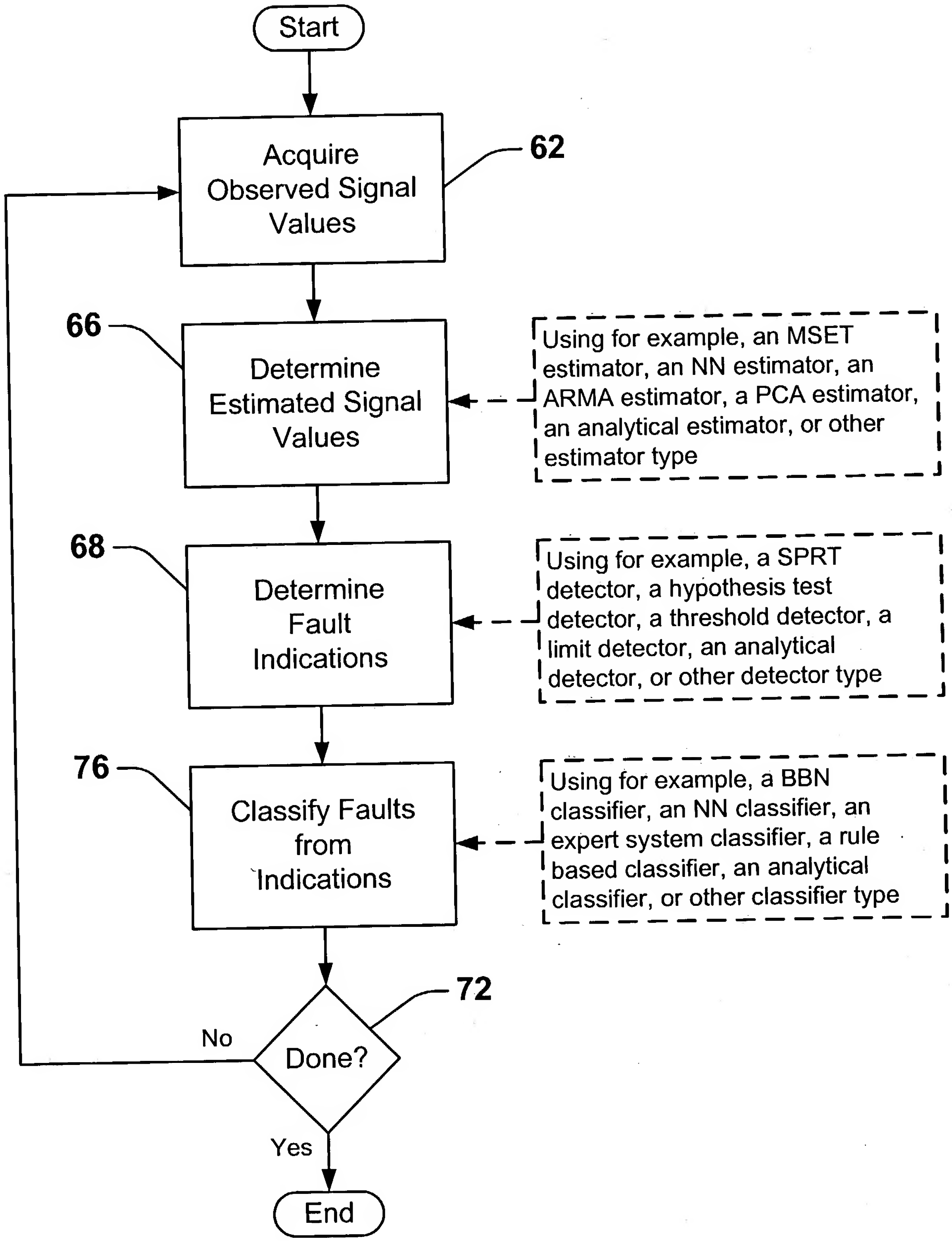

Start
Acquire Observed Signal Values
62
66
Determine Estimated Signal Values
Using for example, an MSET estimator, an NN estimator, an ARMA estimator, a PCA estimator, an analytical estimator, or other estimator type
68
Determine Fault Indications
Using for example, a SPRT detector, a hypothesis test detector, a threshold detector, a limit detector, an analytical detector, or other detector type
76
Classify Faults from Indications
Using for example, a BBN classifier, an NN classifier, an expert system classifier, a rule based classifier, an analytical classifier, or other classifier type
72
No
Done?
Yes
End

Figure 8

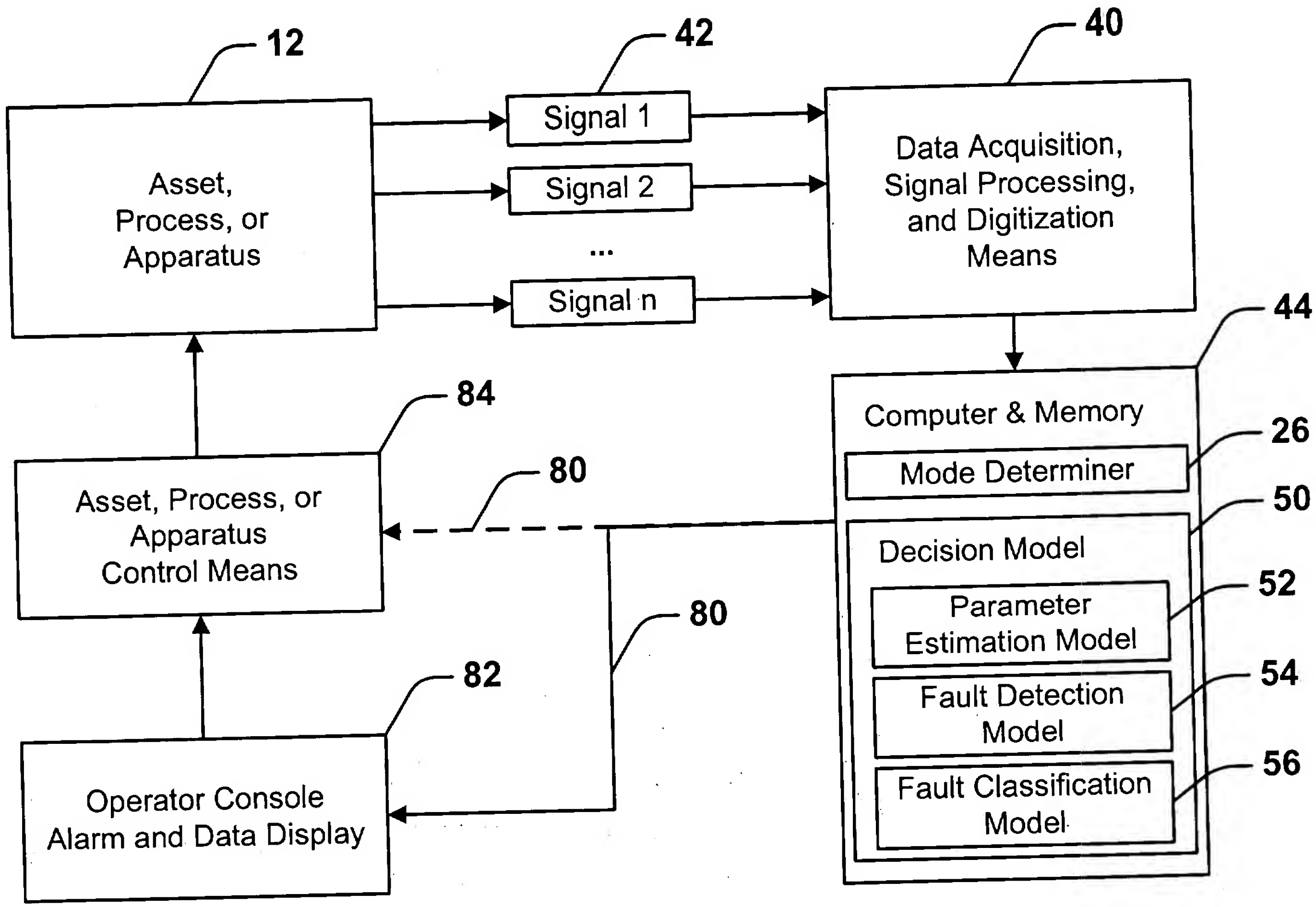
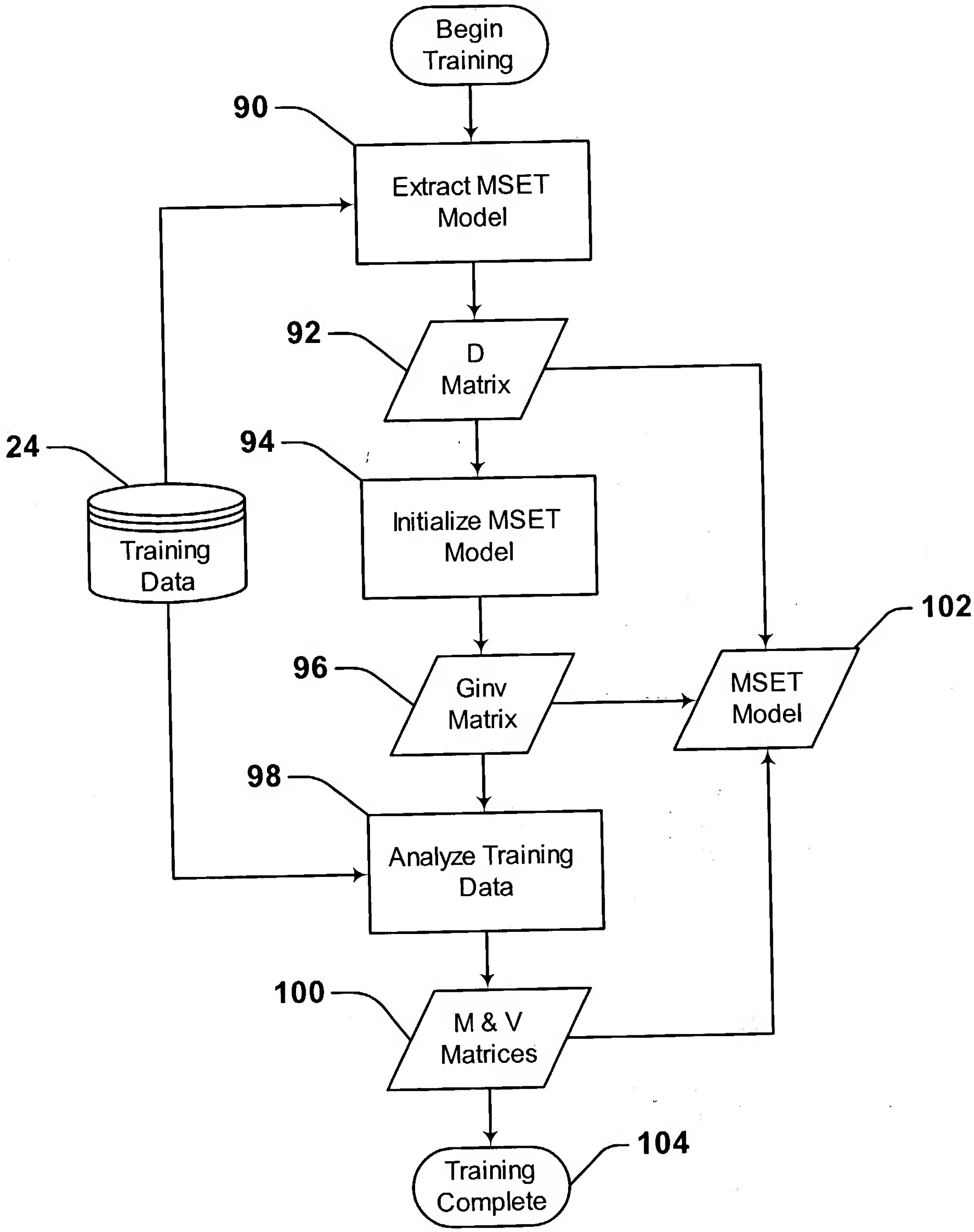
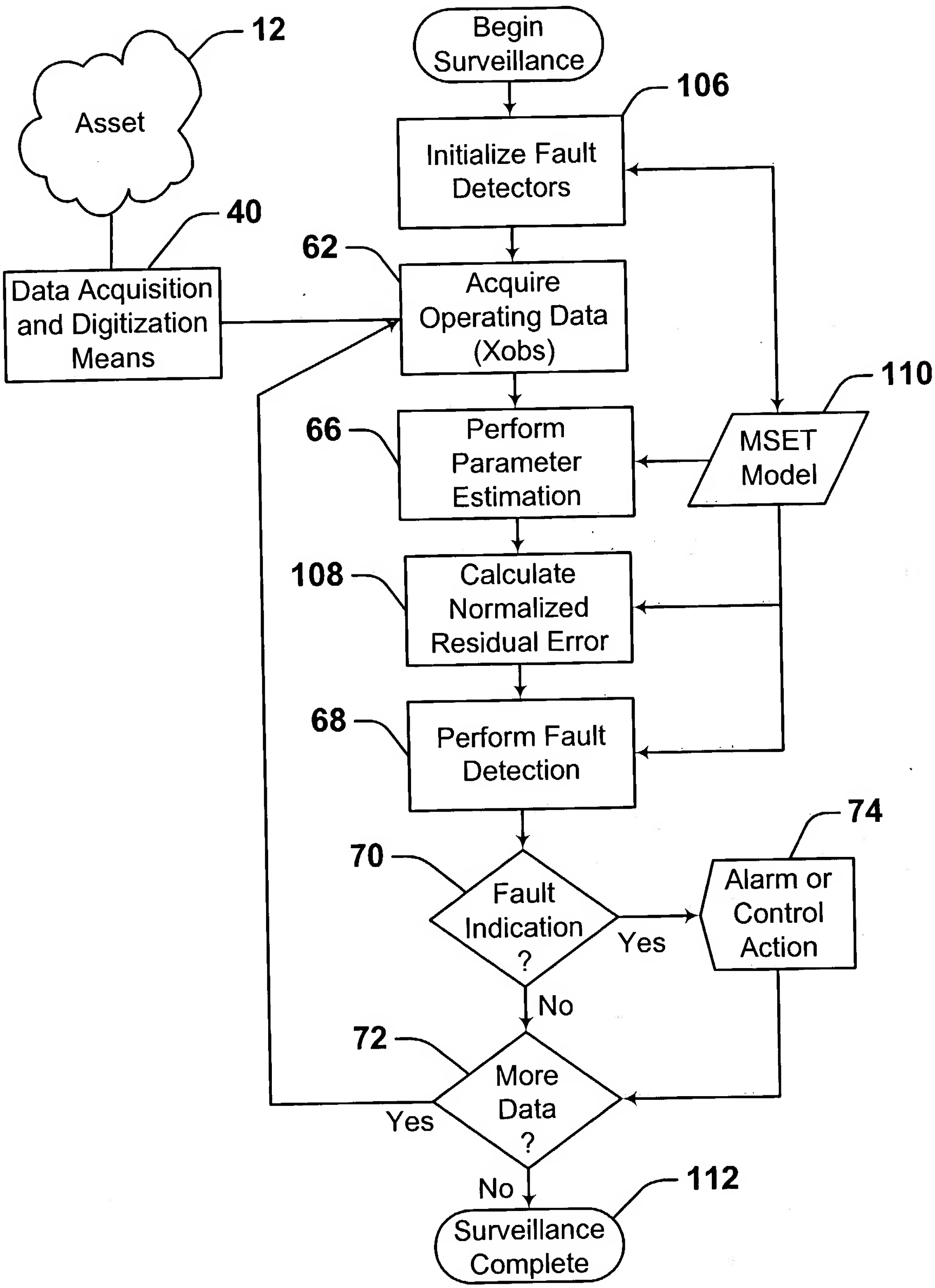

12
Asset, Process, or Apparatus
42
Signal 1
Signal 2
...
Signal n
40
Data Acquisition, Signal Processing, and Digitization Means
44
Computer & Memory
26
Mode Determiner
50
Decision Model
52
Parameter Estimation Model
54
Fault Detection Model
56
Fault Classification Model
84
Asset, Process, or Apparatus Control Means
80
80
82
Operator Console Alarm and Data Display

Figure 9



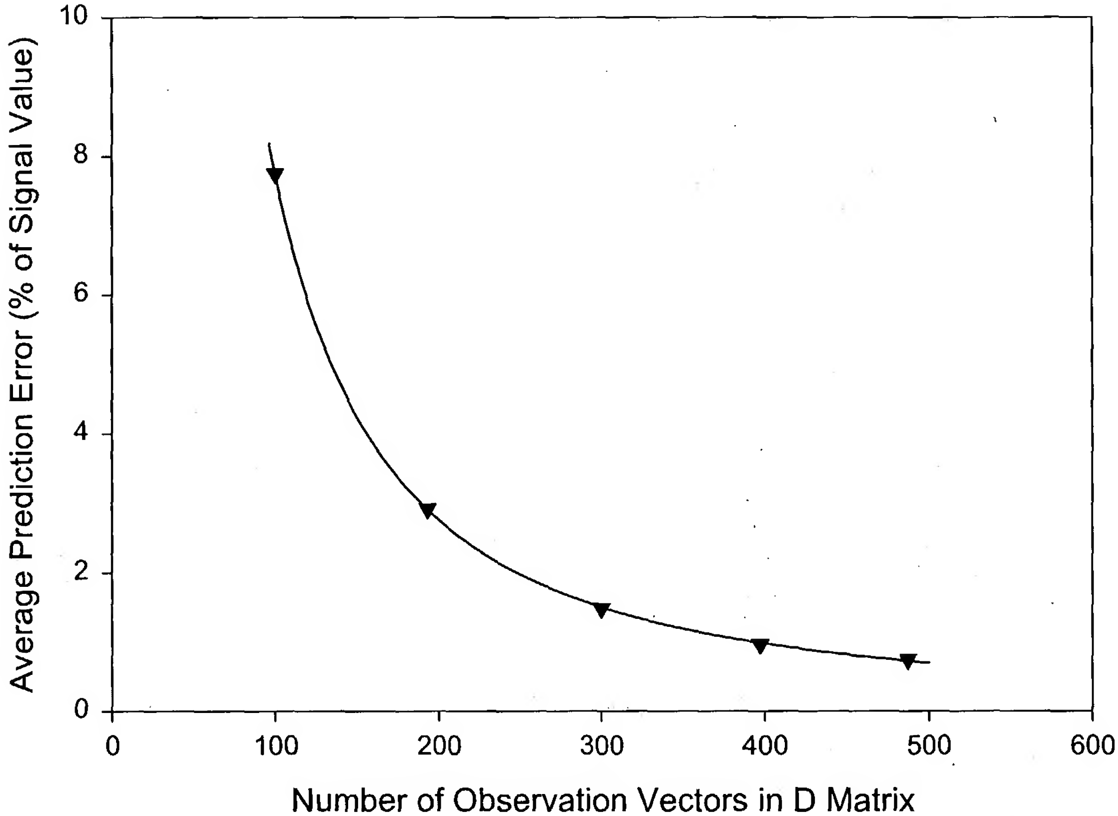
Begin Training
90
Extract MSET Model
92
D Matrix
24
Training Data
94
Initialize MSET Model
96
Ginv Matrix
102
MSET Model
98
Analyze Training Data
100
M & V Matrices
104
Training Complete

Figure 10



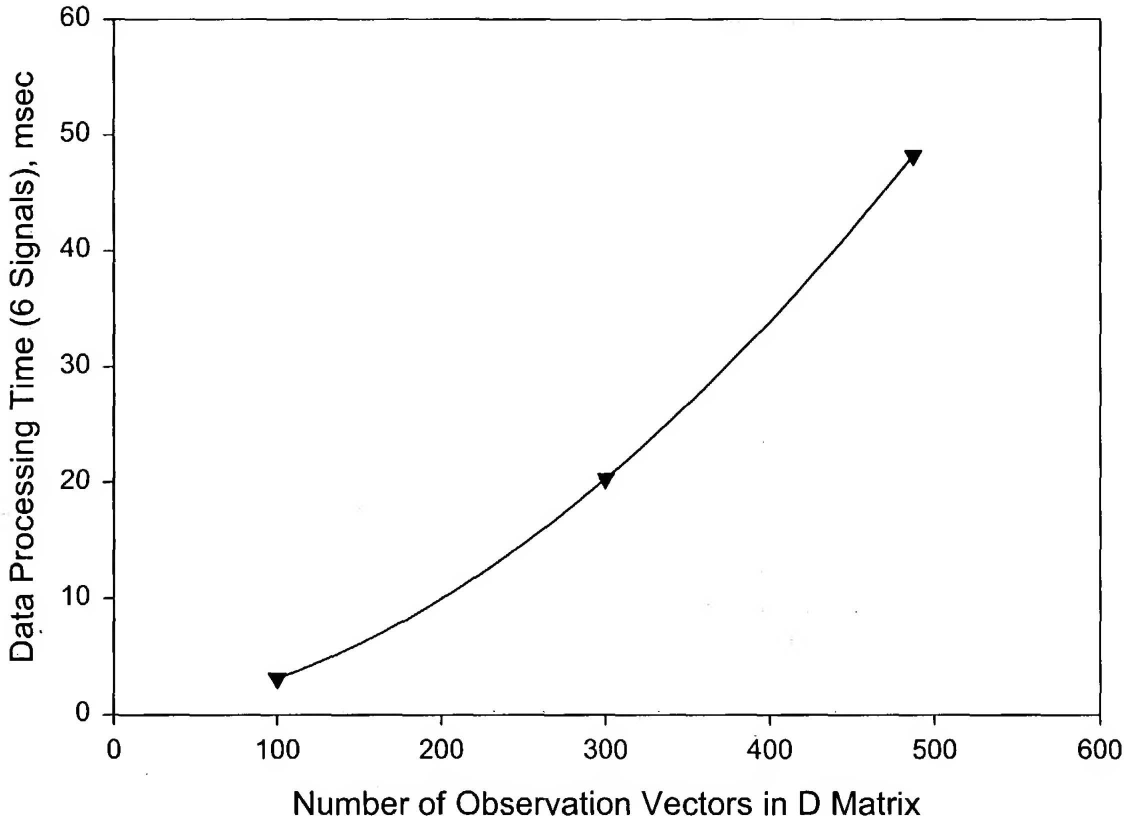
12
Asset
40
Data Acquisition and Digitization Means
Begin Surveillance
106
Initialize Fault Detectors
62
Acquire Operating Data (Xobs)
110
MSET Model
66
Perform Parameter Estimation
108
Calculate Normalized Residual Error
68
Perform Fault Detection
70
Fault Indication ?
Yes
74
Alarm or Control Action
No
72
More Data ?
Yes
No
112
Surveillance Complete

Figure 11



10
8
6
4
2
0
Average Prediction Error (% of Signal Value)
0
100
200
300
400
500
600
Number of Observation Vectors in D Matrix

Figure 12



60
50
40
30
20
10
0
0
100
200
300
400
500
600
Data Processing Time (6 Signals), msec
Number of Observation Vectors in D Matrix

Figure 13

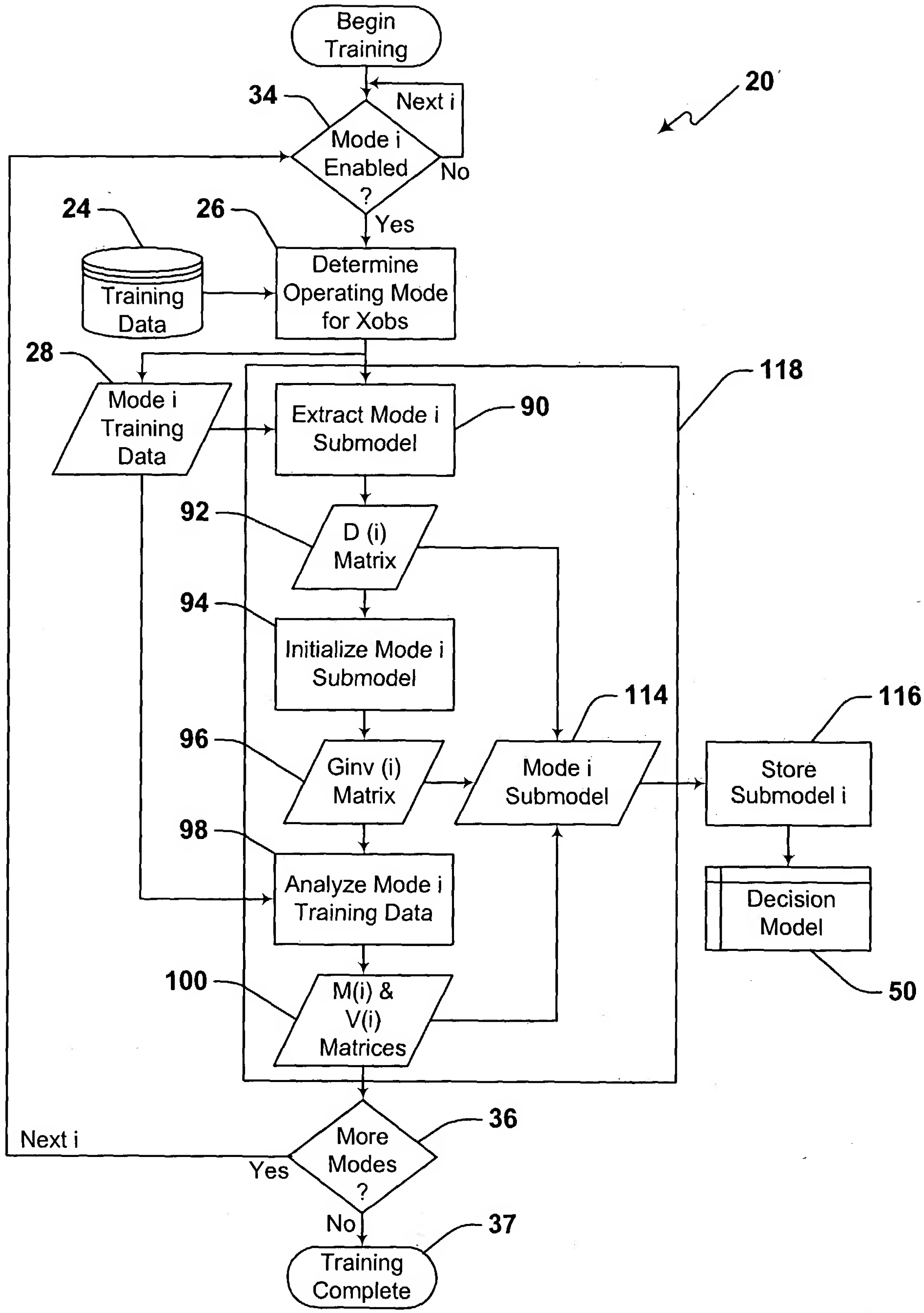

Begin Training
20
34
Next i
Mode i Enabled ?
No
Yes
24
26
Training Data
Determine Operating Mode for Xobs
28
118
Mode i Training Data
Extract Mode i Submodel
90
92
D (i) Matrix
94
Initialize Mode i Submodel
114
116
96
Ginv (i) Matrix
Mode i Submodel
Store Submodel i
98
Analyze Mode i Training Data
Decision Model
100
M(i) & V(i) Matrices
50
36
Next i
More Modes ?
Yes
No
37
Training Complete

Figure 14

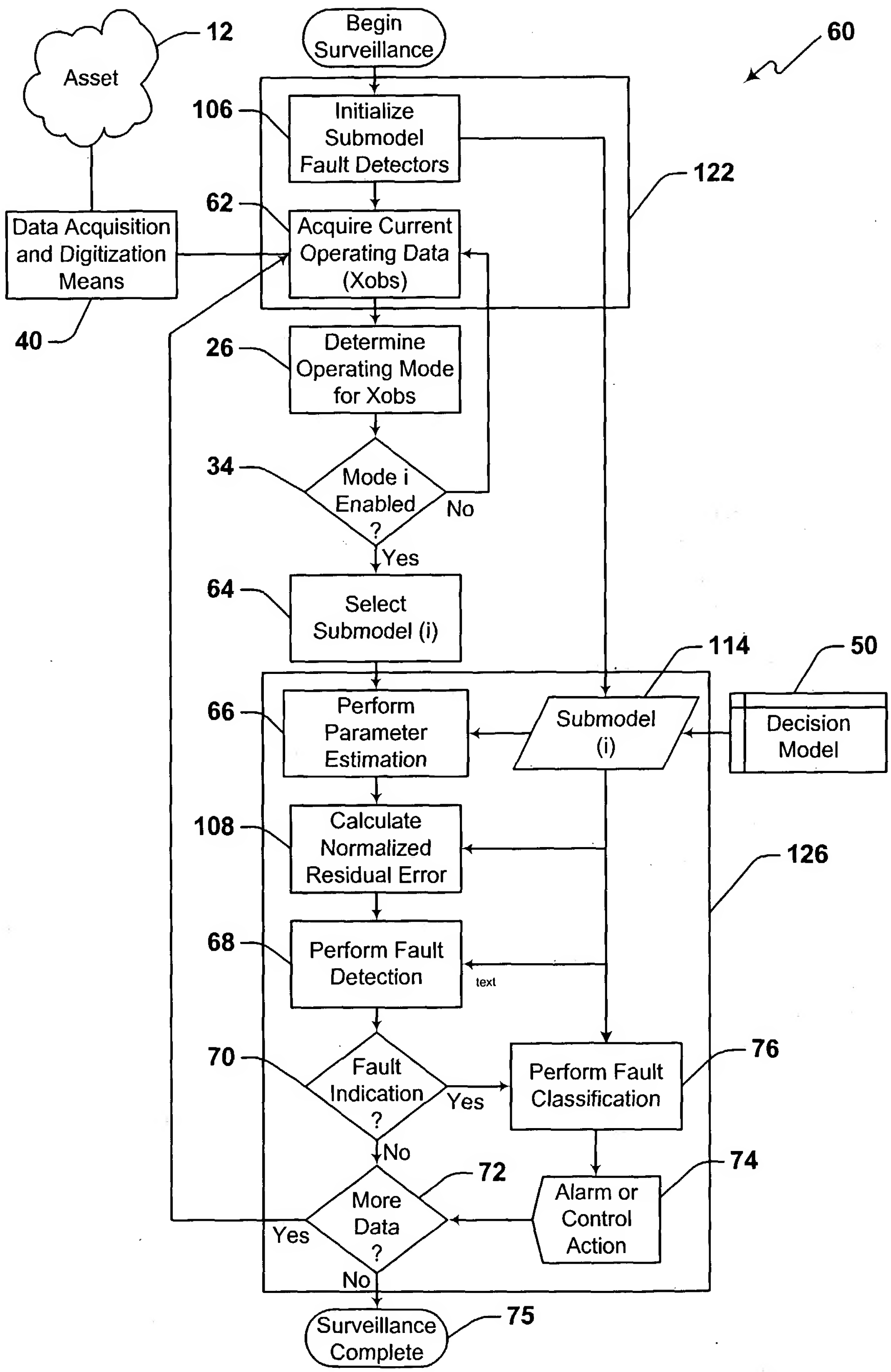

Asset
12
Begin Surveillance
60
106
Initialize Submodel Fault Detectors
122
62
Data Acquisition and Digitization Means
Acquire Current Operating Data (Xobs)
40
26
Determine Operating Mode for Xobs
34
Mode i Enabled ?
No
Yes
64
Select Submodel (i)
114
50
66
Perform Parameter Estimation
Submodel (i)
Decision Model
108
Calculate Normalized Residual Error
126
68
Perform Fault Detection
text
70
Fault Indication ?
Yes
Perform Fault Classification
76
No
72
74
More Data ?
Yes
Alarm or Control Action
No
Surveillance Complete
75

Figure 15

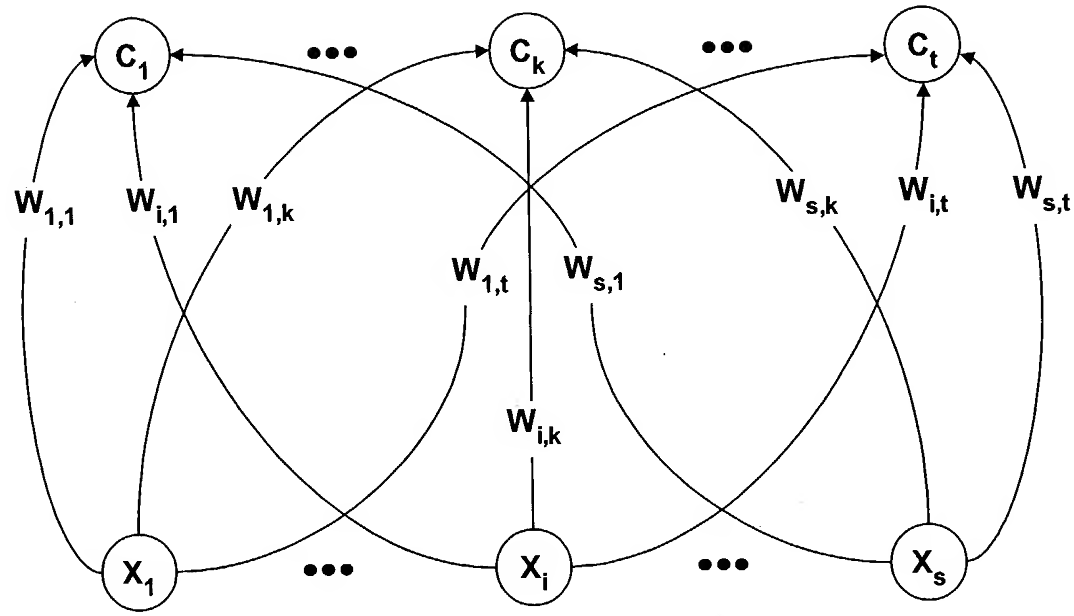


Figure 16

LVQ Neural Network Parameter	Design Value
Input Signals	MCC_PC_AVG (PC_CNTL_REF – MCC_PC_AVG) (ΔPC_CNTL_REF / ΔTIME)
Number of Classes	9 (one for each operating mode defined in Figure 21)
Number of Output Nodes per Class ($\mathbf{N}_{\mathbf{class}}$)	8 (for each operating mode)
Learning Algorithm	LVQ2.1
Maximum Number of Epochs ($\mathbf{n}_{\mathbf{eps}}$)	250
Initial Value of the Learning Rate (λ_0)	0.02
Window Size (ε)	0.5
Number of Training Vector Pairs ($\mathbf{n}_{\mathbf{LVQ}}$)	500

Figure 17

SSME Signal Parameter ID	SSME Signal Parameter Name
PID40	OPOV_ACT_POS_A
PID42	FPOV_ACT_POS_A
PID52	HPFP_DS_P_A
PID58	FPB_PC_A
PID63	MCC_PC_AVG
PID90	HPOP_DS_P
PID100	FUEL_FLOW_AVG
PID105	HPFT_DS_T_A2
PID106	HPFT_DS_T_A3
PID107	HPFT_DS_T_B2
PID108	HPFT_DS_T_B3
PID200	MCC_PC_A_AVG
PID201	MCC_PC_B_AVG
PID205	HPOT_DS_T_A2
PID206	HPOT_DS_T_A3
PID207	HPOT_DS_T_B2
PID208	HPOT_DS_T_B3

Figure 18

Space Shuttle Flight ID	Engine Position
STS077	E2
STS078	E1
STS081	E3
STS082	E1
STS085	E1
STS085	E2
STS086	E2
STS087	E2
STS087	E3
STS090	E1

Figure 19

Model Description	Number of Signals	Modeled Operating Modes	Number of Process Mem Vectors	Parameter Estimation Method	Fault Detection Method
LVQ mode-partitioned (Model PD)	17 (defined in Figure 18)	Start01 Start12 Start24 SteadyFull SteadyLow Upthrust Downthrust	150 150 150 150 150 150 150	MSET	SPRT mean pos & neg
All-modes (Model A150)	17 (same)	All	150	MSET	SPRT mean pos & neg
All-modes (Model A300)	17 (same)	All	300	MSET	SPRT mean pos & neg

Figure 20

<table>
<tr><th>Mode Name</th><th>Operating Mode Criteria</th></tr>
<tr><td>PREFIRE</td><td>All observations preceding the vehicle start command to the engine. Considered a non-operating mode.</td></tr>
<tr><td>START01</td><td>Controller cycles 0 through 24 after receipt of the engine start command.</td></tr>
<tr><td>START12</td><td>Controller cycles 25 through 49 after receipt of the engine start command.</td></tr>
<tr><td>START24</td><td>Controller cycle 50 through detection of steady-state operation (typically at controller cycle ~110). The rule for transition to STEADY_FULL is: If in START24 and if
|PC_CNTL_REF – MCC_PC_AVG | <= (5 * 3.35), and
PC_CNTL_REF >= 2500 transition to STEADY_FULL</td></tr>
<tr><td>STEADY_FULL</td><td>STEADY_FULL is declared when either: 1) the last cycle's state was STEADY_FULL and the commanded PC is both unchanged and greater than 2500 psi, e.g.,
| PC_CNTL_REF –LAST_PC_CNTL_REF | < 3.35 and
PC_CNTL_REF >= 2500;
or 2) when the last cycle's state was a transient state and
| PC_CNTL_REF – MCC_PC_AVG | <= (5 * 3.35) and
PC_CNTL_REF >= 2500.</td></tr>
<tr><td>STEADY_LOW</td><td>STEADY_LOW is declared when either: 1) the last cycle's state was STEADY_LOW and the commanded PC is both unchanged and less than 2500 psi, e.g.,
| PC_CNTL_REF –LAST_PC_CNTL_REF | < 3.35 and
PC_CNTL_REF < 2500;
or 2) when the last cycle's state was a transient state and
| PC_CNTL_REF – MCC_PC_AVG | <= (5 * 3.35) and
PC_CNTL_REF < 2500.</td></tr>
<tr><td>UPTHRUST</td><td>UPTHRUST is declared when 1) the commanded PC has increased since the last cycle, and 2)
| PC_CNTL_REF – MCC_PC_AVG | > (5 * 3.35)</td></tr>
<tr><td>DOWNTHRUST</td><td>DOWNTHRUST is declared when 1) the commanded PC has decreased since the last cycle, and 2)
| PC_CNTL_REF – MCC_PC_AVG | > (5 * 3.35)</td></tr>
<tr><td>SHUTDOWN</td><td>All observations following the vehicle shutdown command to the engine. Considered a non-operating mode.</td></tr>
</table>

Figure 21

Test No.	Test Description	Sensor Failures	One Cycle Alarms	Total Avg Error %	Avg Cycle Time
PD-01	STS077E1. Nominal flight data.	0	2	0.408%	4.88 msec
PD-02	STS077E2. Nominal flight data.	0	0	0.217%	4.90 msec
PD-03	STS078E1. Nominal flight data.	0	0	0.352%	4.98 msec
PD-04	STS078E2. Nominal flight data.	0	1	0.296%	4.94 msec
PD-05	STS081E1. Nominal flight data.	0	2	0.400%	5.01 msec
PD-06	STS081E3. Nominal flight data.	0	0	0.281%	5.07 msec
PD-07	STS082E2. Nominal flight data.	0	1	0.286%	4.96 msec
PD-08	STS085E3. Nominal flight data.	0	0	0.282%	4.98 msec
PD-09	STS086E2. Nominal flight data.	0	0	0.254%	5.02 msec
PD-10	STS087E2. Nominal flight data.	0	0	0.246%	5.02 msec
	Average for All Tests	*0*	*1*	*0.302%*	*4.98 msec*

Figure 22

T t No.	T st D scription	S nsor Failures	On Cycle Alarms	Tim to Detect	Error at Detect
PD-11	Drift PID40. 0.14 pct/sec beginning at 10.0 sec.	1 (PID40)	5	28.88 sec	5.8%
PD-12	Noise PID40. ±5 pct random beginning at 10.0 sec.	1 (PID40)	38	10.76 sec	N/A
PD-13	Drift PID42. 0.16 pct/sec beginning at 10.0 sec.	1 (PID42)	9	29.32 sec	5.9%
PD-14	Noise PID42. ±5 pct random beginning at 10.0 sec.	1 (PID42)	66	42.04 sec	N/A
PD-15	Drift PID52. 11.9 psi/sec beginning at 10.0 sec.	1 (PID52)	4	12.24 sec	2.4%
PD-16	Drift PID58. 10.2 psi/sec beginning at 10.0 sec.	1 (PID58)	5	9.44 sec	1.9%
PD-17	Drift PID90. 8.2 psi/sec beginning at 10.0 sec.	1 (PID90)	9	8.12 sec	1.6%
PD-18	Drift PID100. 31.9 gpm/sec beginning at 10.0 sec.	1 (PID100)	5	12.12 sec	2.4%
PD-19	Drift PID105. 3.4 degR/sec beginning at 10.0 sec.	1 (PID105)	11	16.16 sec	3.2%
PD-20	Drift PID200. 6.3 psi/sec beginning at 10.0 sec.	1 (PID200)	4	3.40 sec	0.7%
PD-21	Drift PID205. 2.7 degR/sec beginning at 10.0 sec.	1 (PID205)	4	18.28 sec	3.7%
	Average for All Drift Tests			*15.3 sec*	*3.1%*

Figure 23

Test No.	Test Description	S_nsor Failures	One Cycl_ Alarms	Total Avg Error %	Avg Cycle Time
A150-01	STS077E1. Nominal flight data.	0	0	0.556%	5.27 msec
A150-02	STS077E2. Nominal flight data.	0	9	0.458%	5.28 msec
A150-03	STS078E1. Nominal flight data.	0	0	0.593%	4.90 msec
A150-04	STS078E2. Nominal flight data.	0	0	0.396%	5.28 msec
A150-05	STS081E1. Nominal flight data.	0	0	0.685%	4.67 msec
A150-06	STS081E3. Nominal flight data.	0	0	0.480%	4.77 msec
A150-07	STS082E2. Nominal flight data.	1 (PID58) False Alarm	13	0.720%	5.28 msec
A150-08	STS085E3. Nominal flight data.	0	0	0.519%	4.73 msec
A150-09	STS086E2. Nominal flight data.	0	0	0.410%	4.77 msec
A150-10	STS087E2. Nominal flight data.	0	0	0.399%	5.22 msec
	Average for All Tests	*0*	*2*	*0.522%*	*5.02 msec*

Figure 24. Comparative Results

Test No.	Test Description	S nsor Failures	One Cycl Alarms	Time to Detect	Error at Detect
A150-11	Drift PID40. 0.14 pct/sec beginning at 10.0 sec.	1 (PID40)	19	125.68 sec	25.1%
A150-12	Noise PID40. ±5 pct random beginning at 10.0 sec.	1 (PID40)	12	95.04 sec	N/A
A150-13	Drift PID42. 0.16 pct/sec beginning at 10.0 sec.	1 (PID42)	12	154.92 sec	31.0%
A150-14	Noise PID42. ±5 pct random beginning at 10.0 sec.	0 (Missed Alarm)	0	Missed Alarm	N/A
A150-15	Drift PID52. 11.9 psi/sec beginning at 10.0 sec.	1 (PID52)	4	27.40 sec	5.5%
A150-16	Drift PID58. 10.2 psi/sec beginning at 10.0 sec.	1 (PID58)	6	18.92 sec	3.8%
A150-17	Drift PID90. 8.2 psi/sec beginning at 10.0 sec.	1 (PID90)	4	60.32 sec	12.1%
A150-18	Drift PID100. 31.9 gpm/sec beginning at 10.0 sec.	2 (PID100) & (PID58 False Alarm)	23	43.24 sec	8.6%
A150-19	Drift PID105. 3.4 degR/sec beginning at 10.0 sec.	1 (PID105)	10	46.20 sec	9.2%
A150-20	Drift PID200. 6.3 psi/sec beginning at 10.0 sec.	1 (PID200)	4	22.72 sec	4.5%
A150-21	Drift PID205. 2.7 degR/sec beginning at 10.0 sec.	1 (PID205)	8	89.04 sec	17.8%
	Average for All Drift Tests			*65.4 sec*	*13.1%*

Figure 25. Comparative Results

Test No.	Test Description	Sensor Failures	One Cycle Alarms	Total Avg Error %	Avg Cycle Time
A300-01	STS077E1. Nominal flight data.	0	0	0.488%	17.84 msec
A300-02	STS077E2. Nominal flight data.	0	0	0.379%	17.75 msec
A300-03	STS078E1. Nominal flight data.	0	0	0.424%	19.40 msec
A300-04	STS078E2. Nominal flight data.	0	0	0.359%	19.02 msec
A300-05	STS081E1. Nominal flight data.	0	0	0.633%	17.69 msec
A300-06	STS081E3. Nominal flight data.	0	0	0.501%	17.80 msec
A300-07	STS082E2. Nominal flight data.	0	0	0.620%	19.01 msec
A300-08	STS085E3. Nominal flight data.	0	2	0.521%	17.73 msec
A300-09	STS086E2. Nominal flight data.	0	1	0.340%	17.78 msec
A300-10	STS087E2. Nominal flight data.	0	0	0.319%	18.10 msec
	Average for All Tests	*0*	*0*	*0.458%*	*18.21 msec*

Figure 26. Comparative Results

Test No.	Test Description	Sensor Failures	One Cycle Alarms[1]	Time to Detect	Error at Detect
A300-11	Drift PID40. 0.14 pct/sec beginning at 10.0 sec.	1 (PID40)	39	138.80 sec	27.8%
A300-12	Noise PID40. ±5 pct random beginning at 10.0 sec.	0 (Missed Alarm)	2	Missed Alarm	N/A
A300-13	Drift PID42. 0.16 pct/sec beginning at 10.0 sec.	1 (PID42)	26	139.08 sec	27.8%
A300-14	Noise PID42. ±5 pct random beginning at 10.0 sec.	0 (Missed Alarm)	2	Missed Alarm	N/A
A300-15	Drift PID52. 11.9 psi/sec beginning at 10.0 sec.	1 (PID52)	9	26.04 sec	5.2%
A300-16	Drift PID58. 10.2 psi/sec beginning at 10.0 sec.	1 (PID58)	8	16.92 sec	3.4%
A300-17	Drift PID90. 8.2 psi/sec beginning at 10.0 sec.	1 (PID90)	6	58.12 sec	11.6%
A300-18	Drift PID100. 31.9 gpm/sec beginning at 10.0 sec.	1 (PID100)	9	23.36 sec	4.7%
A300-19	Drift PID105. 3.4 degR/sec beginning at 10.0 sec.	1 (PID105)	6	28.32 sec	5.7%
A300-20	Drift PID200. 6.3 psi/sec beginning at 10.0 sec.	1 (PID200)	6	18.52 sec	3.7%
A300-21	Drift PID205. 2.7 degR/sec beginning at 10.0 sec.	1 (PID205)	12	64.32 sec	12.9%
	Average for All Drift Tests			*57.1 sec*	*11.4%*

Figure 27. Comparative Results

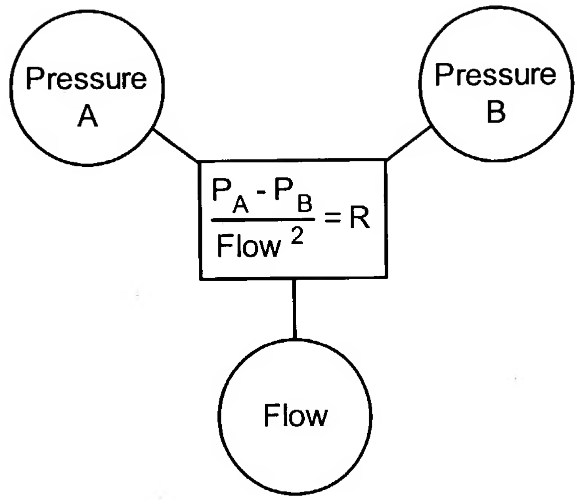


Figure 28

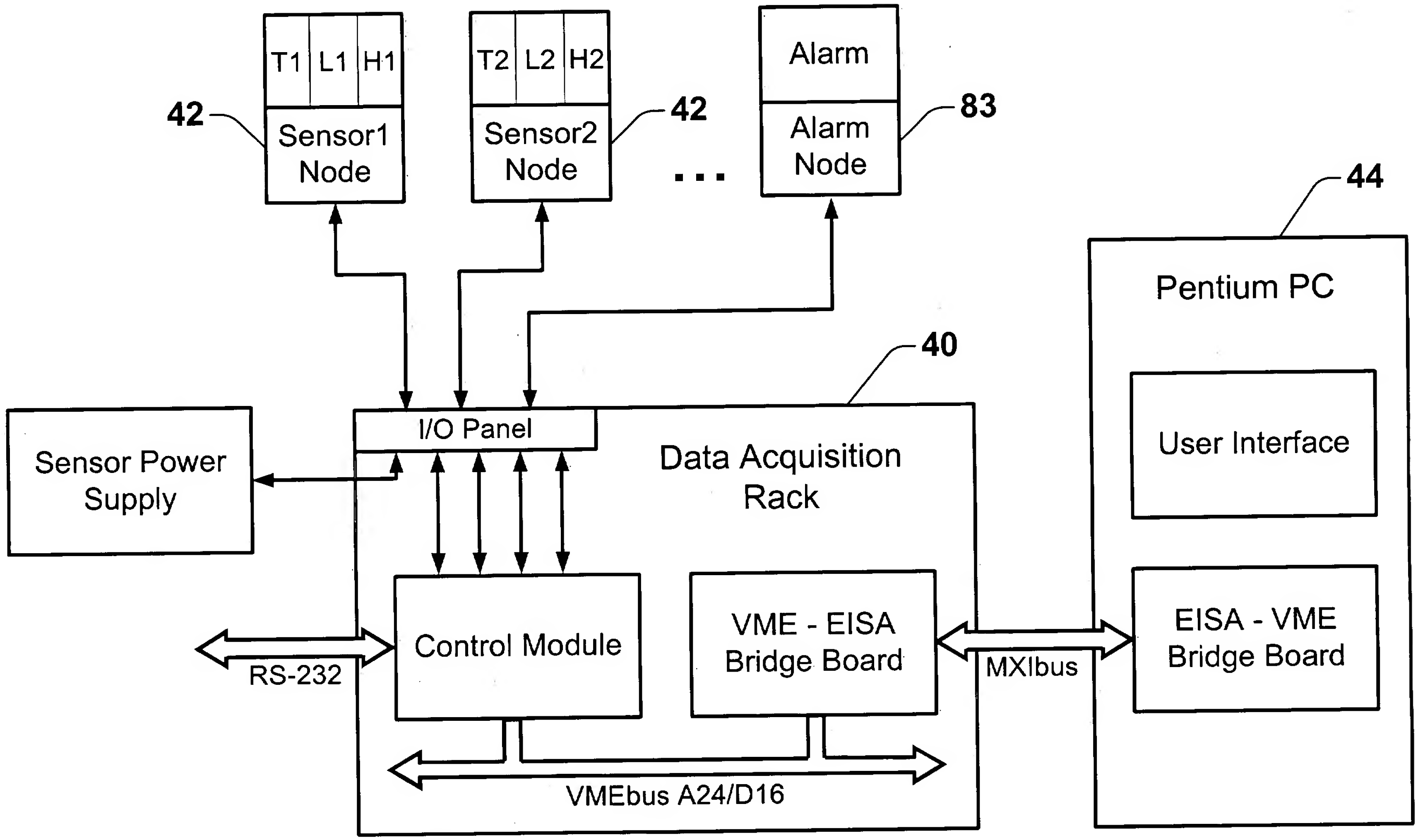

T1
L1
H1
Sensor1 Node
42
T2
L2
H2
Sensor2 Node
42
Alarm
Alarm Node
83
44
Pentium PC
User Interface
EISA - VME Bridge Board
40
I/O Panel
Data Acquisition Rack
Sensor Power Supply
Control Module
VME - EISA Bridge Board
RS-232
MXIbus
VMEbus A24/D16

Figure 29

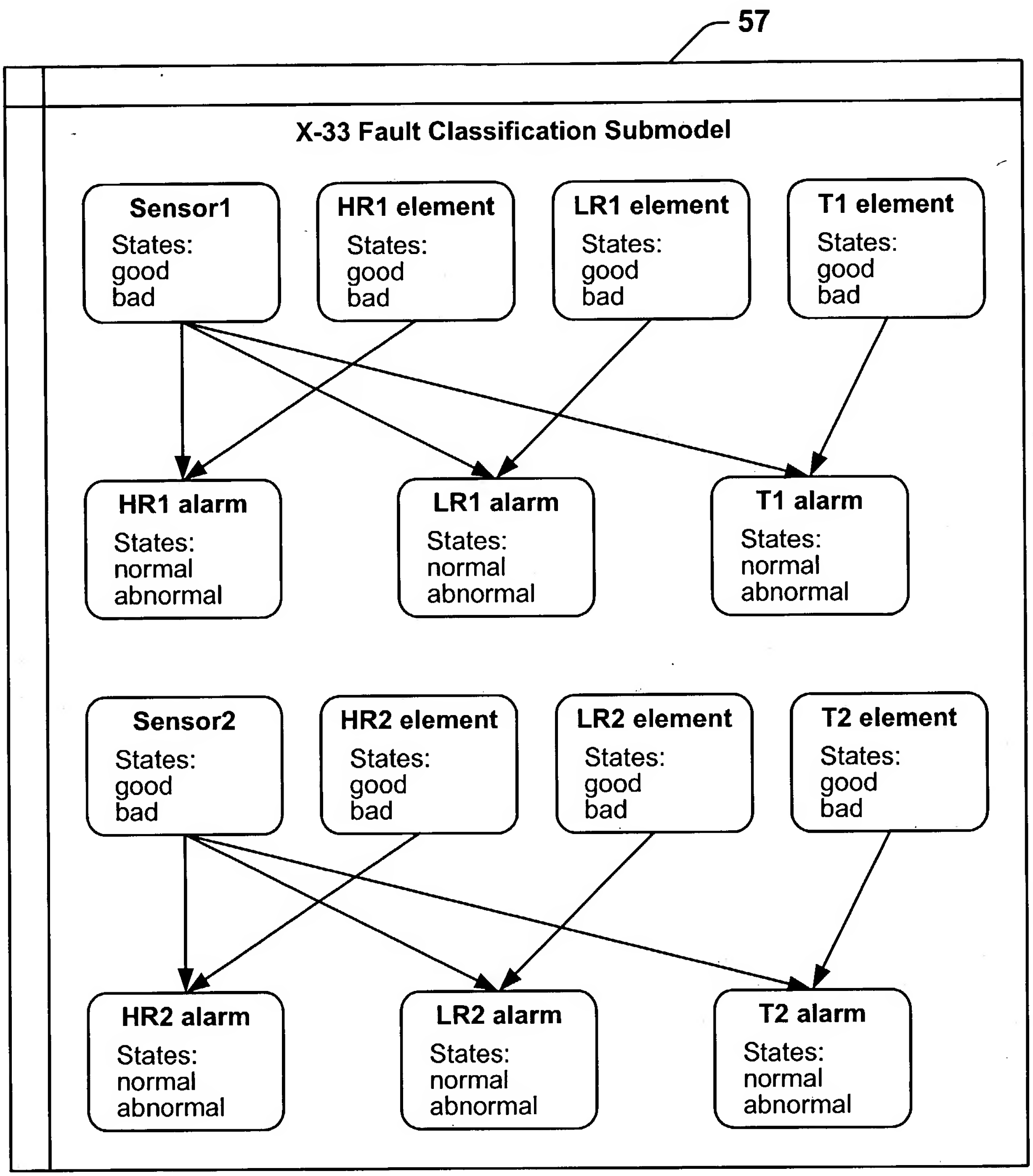

57
X-33 Fault Classification Submodel
Sensor1
States:
good
bad
HR1 element
States:
good
bad
LR1 element
States:
good
bad
T1 element
States:
good
bad
HR1 alarm
States:
normal
abnormal
LR1 alarm
States:
normal
abnormal
T1 alarm
States:
normal
abnormal
Sensor2
States:
good
bad
HR2 element
States:
good
bad
LR2 element
States:
good
bad
T2 element
States:
good
bad
HR2 alarm
States:
normal
abnormal
LR2 alarm
States:
normal
abnormal
T2 alarm
States:
normal
abnormal

Figure 30

<table>
<tr><th>Node Name</th><th>States</th><th>Parents</th><th>Prior Probabilities</th><th>Threshold</th></tr>
<tr><td>Sensor1</td><td>good
bad</td><td>none</td><td>P(good)=0.95, P(bad)=0.05</td><td>0.6</td></tr>
<tr><td>HR1 element</td><td>good
bad</td><td>none</td><td>P(good)=0.9, P(bad)=0.1</td><td>0.6</td></tr>
<tr><td>LR1 element</td><td>good
bad</td><td>none</td><td>P(good)=0.9, P(bad)=0.1</td><td>0.6</td></tr>
<tr><td>T1 element</td><td>good
bad</td><td>none</td><td>P(good)=0.9, P(bad)=0.1</td><td>0.6</td></tr>
<tr><td>HR1 alarm</td><td>normal
abnormal</td><td>HR1 element
Sensor1</td><td>P(normal | HR1 element=good, Sensor1=good)=0.95
P(abnormal | HR1 element=good, Sensor1=good)=0.05
P(normal | HR1 element=good, Sensor1=bad)=0.05
P(abnormal | HR1 element=good, Sensor1=bad)=0.95
P(normal | HR1 element=bad, Sensor1=good)=0.05
P(abnormal | HR1 element=bad, Sensor1=good)=0.95
P(normal | HR1 element=bad, Sensor1=bad)=0.01
P(abnormal | HR1 element=bad, Sensor1=bad)=0.99</td><td>0.9</td></tr>
<tr><td>LR1 alarm</td><td>normal
abnormal</td><td>LR1 element
Sensor1</td><td>P(normal | LR1 element=good, Sensor1=good)=0.95
P(abnormal | LR1 element=good, Sensor1=good)=0.05
P(normal | LR1 element=good, Sensor1=bad)=0.05
P(abnormal | LR1 element=good, Sensor1=bad)=0.95
P(normal | LR1 element=bad, Sensor1=good)=0.05
P(abnormal | LR1 element=bad, Sensor1=good)=0.95
P(normal | LR1 element=bad, Sensor1=bad)=0.01
P(abnormal | LR1 element=bad, Sensor1=bad)=0.99</td><td>0.9</td></tr>
<tr><td>T1 alarm</td><td>normal
abnormal</td><td>T1 element
Sensor1</td><td>P(normal | T1 element=good, Sensor1=good)=0.95
P(abnormal | T1 element=good, Sensor1=good)=0.05
P(normal | T1 element=good, Sensor1=bad)=0.05
P(abnormal | T1 element=good, Sensor1=bad)=0.95
P(normal | T1 element=bad, Sensor1=good)=0.05
P(abnormal | T1 element=bad, Sensor1=good)=0.95
P(normal | T1 element=bad, Sensor1=bad)=0.01
P(abnormal | T1 element=bad, Sensor1=bad)=0.99</td><td>0.9</td></tr>
</table>

Figure 31

<table>
<tr><th>Node Name</th><th>States</th><th>Parents</th><th>Prior Probabilities</th><th>Threshold</th></tr>
<tr><td>Sensor2</td><td>good
bad</td><td>none</td><td>P(good)=0.95, P(bad)=0.05</td><td>0.6</td></tr>
<tr><td>HR2 element</td><td>good
bad</td><td>none</td><td>P(good)=0.9, P(bad)=0.1</td><td>0.6</td></tr>
<tr><td>LR2 element</td><td>good
bad</td><td>none</td><td>P(good)=0.9, P(bad)=0.1</td><td>0.6</td></tr>
<tr><td>T2 element</td><td>good
bad</td><td>none</td><td>P(good)=0.9, P(bad)=0.1</td><td>0.6</td></tr>
<tr><td>HR2 alarm</td><td>normal
abnormal</td><td>HR2 element
Sensor2</td><td>P(normal | HR2 element=good, Sensor2=good)=0.95
P(abnormal | HR2 element=good, Sensor2=good)=0.05
P(normal | HR2 element=good, Sensor2=bad)=0.05
P(abnormal | HR2 element=good, Sensor2=bad)=0.95
P(normal | HR2 element=bad, Sensor2=good)=0.05
P(abnormal | HR2 element=bad, Sensor2=good)=0.95
P(normal | HR2 element=bad, Sensor2=bad)=0.01
P(abnormal | HR2 element=bad, Sensor2=bad)=0.99</td><td>0.9</td></tr>
<tr><td>LR2 alarm</td><td>normal
abnormal</td><td>LR2 element
Sensor2</td><td>P(normal | LR2 element=good, Sensor2=good)=0.95
P(abnormal | LR2 element=good, Sensor2=good)=0.05
P(normal | LR2 element=good, Sensor2=bad)=0.05
P(abnormal | LR2 element=good, Sensor2=bad)=0.95
P(normal | LR2 element=bad, Sensor2=good)=0.05
P(abnormal | LR2 element=bad, Sensor2=good)=0.95
P(normal | LR2 element=bad, Sensor2=bad)=0.01
P(abnormal | LR2 element=bad, Sensor2=bad)=0.99</td><td>0.9</td></tr>
<tr><td>T2 alarm</td><td>normal
abnormal</td><td>T2 element
Sensor2</td><td>P(normal | T2 element=good, Sensor2=good)=0.95
P(abnormal | T2 element=good, Sensor2=good)=0.05
P(normal | T2 element=good, Sensor2=bad)=0.05
P(abnormal | T2 element=good, Sensor2=bad)=0.95
P(normal | T2 element=bad, Sensor2=good)=0.05
P(abnormal | T2 element=bad, Sensor2=good)=0.95
P(normal | T2 element=bad, Sensor2=bad)=0.01
P(abnormal | T2 element=bad, Sensor2=bad)=0.99</td><td>0.9</td></tr>
</table>

Figure 32

Partitioned Model Under OPERATING Conditions		
Fault Simulated	**Fault Classified**	**Fault Classification Probabilities**
H1 Drift High	H1 Element Fault	P(H1 Element = ABNORMAL)= 0.6779 P(L1 Element = ABNORMAL)= 0.0058 P(T1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
L1 Drift High	L1 Element Fault	P(L1 Element = ABNORMAL)= 0.6779 P(H1 Element = ABNORMAL)= 0.0058 P(T1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
T1 Drift High	T1 Element Fault	P(T1 Element = ABNORMAL)= 0.6779 P(H1 Element = ABNORMAL)= 0.0058 P(L1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
H1 & L1 Drift High	H1 Element Fault L1 Element Fault	P(H1 Element = ABNORMAL)= 0.6121 P(L1 Element = ABNORMAL)= 0.6121 P(Sensor1= ABNORMAL)= 0.1156 P(T1 Element = ABNORMAL)= 0.0077
H1, L1 & T1 Drift High	Sensor1 Fault	P(Sensor1= ABNORMAL)= 0.9433 P(H1 Element = ABNORMAL)= 0.1363 P(L1 Element = ABNORMAL)= 0.1363 P(T1 Element = ABNORMAL)= 0.1363

Figure 33

Partitioned Model Under VENTING Conditions		
Fault Simulated	**Fault Classified**	**Fault Classification Probabilities**
H1 Drift High	H1 Element Fault	P(H1 Element = ABNORMAL)= 0.6779 P(L1 Element = ABNORMAL)= 0.0058 P(T1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
L1 Drift High	L1 Element Fault	P(L1 Element = ABNORMAL)= 0.6779 P(H1 Element = ABNORMAL)= 0.0058 P(T1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
T1 Drift High	T1 Element Fault	P(T1 Element = ABNORMAL)= 0.6779 P(H1 Element = ABNORMAL)= 0.0058 P(L1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
H1 & L1 Drift High	H1 Element Fault L1 Element Fault	P(H1 Element = ABNORMAL)= 0.6121 P(L1 Element = ABNORMAL)= 0.6121 P(Sensor1= ABNORMAL)= 0.1156 P(T1 Element = ABNORMAL)= 0.0077
H1, L1 & T1 Drift High	Sensor1 Fault	P(Sensor1= ABNORMAL)= 0.9433 P(H1 Element = ABNORMAL)= 0.1363 P(L1 Element = ABNORMAL)= 0.1363 P(T1 Element = ABNORMAL)= 0.1363

Figure 34

Unpartitioned Model Under OPERATING Conditions		
Fault Simulated	**Fault Classified**	**Fault Classification Probabilities**
H1 Drift High	H1 Element Fault	P(H1 Element = ABNORMAL)= 0.6779 P(L1 Element = ABNORMAL)= 0.0058 P(T1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
L1 Drift High	L1 Element Fault	P(L1 Element = ABNORMAL)= 0.6779 P(H1 Element = ABNORMAL)= 0.0058 P(T1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
T1 Drift High	T1 Element Fault	P(T1 Element = ABNORMAL)= 0.6779 P(H1 Element = ABNORMAL)= 0.0058 P(L1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
H1 & L1 Drift High	H1 Element Fault L1 Element Fault	P(H1 Element = ABNORMAL)= 0.6121 P(L1 Element = ABNORMAL)= 0.6121 P(Sensor1= ABNORMAL)= 0.1156 P(T1 Element = ABNORMAL)= 0.0077
H1, L1 & T1 Drift High	Sensor1 Fault	P(Sensor1= ABNORMAL)= 0.9433 P(H1 Element = ABNORMAL)= 0.1363 P(L1 Element = ABNORMAL)= 0.1363 P(T1 Element = ABNORMAL)= 0.1363

Figure 35 Comparative Results

Unpartitioned Model Under VENTING Conditions		
Fault Simulated	**Fault Classified**	**Fault Classification Probabilities**
H1 Drift High	H1 Element Fault	P(H1 Element = ABNORMAL)= 0.6779 P(L1 Element = ABNORMAL)= 0.0058 P(T1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
L1 Drift High	*Not Detected*	P(L1 Element = ABNORMAL)= 0.1000 P(H1 Element = ABNORMAL)= 0.1000 P(T1 Element = ABNORMAL)= 0.1000 P(Sensor1= ABNORMAL)= 0.0500
T1 Drift High	T1 Element Fault	P(T1 Element = ABNORMAL)= 0.6779 P(H1 Element = ABNORMAL)= 0.0058 P(L1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
H1 & L1 Drift High	H1 Element Fault (L1 Fault Not Detected)	P(H1 Element = ABNORMAL)= 0.6779 P(L1 Element = ABNORMAL)= 0.0058 P(T1 Element = ABNORMAL)= 0.0058 P(Sensor1= ABNORMAL)= 0.0010
H1, L1 & T1 Drift High	H1 Element Fault T1 Element Fault (L1 Fault Not Detected)	P(H1 Element = ABNORMAL)= 0.6121 P(T1 Element = ABNORMAL)= 0.6121 P(Sensor1= ABNORMAL)= 0.1156 P(L1 Element = ABNORMAL)= 0.0077

Figure 36 Comparative Results